SUPPORTING INFORMATION FOR:

Giljum, S., H. Wieland, S. Lutter, N. Eisenmenger, H. Schandl and A. Owen. 2018.The impacts of data deviations between MRIO models on material footprints: A comparison of EXIOBASE, Eora and ICIO. *Journal of Industrial Ecology.*

Summary

This supporting information provides a range of additional information and results: (1) A detailed description of the three GMRIO databases used for this study；(2) tables with countries and sectors in the common classification；(3) detailed descriptions of the SDA and SPLD methods；(4) a comparison of country results in full and cc classifications；(5) the Raw Material Trade Balance (RTB) calculated with the three GMRIO models；(6) a comparison of the material footprint per capita of the model pairs in the common classification；(7) the SDA and SPLD analysis results for Russia；(8) the SPLD results for the additional model pairs for both the Netherlands and Russia.

1. Detailed description of the three GMRIO databases

This study applies three of the most frequently applied GMIRO databases: EXIOBASE, Eora and ICIO. Detailed descriptions of the three databases are provided below.

It is important to note that also other GMRIO databases would be available to perform this type of analysis, notably WIOD (Dietzenbacher et al., 2013) and GTAP (Narayanan et al., 2015). These two databases have not been included due to the following reasons:

- WIOD has a low detail with regard to raw material extraction sectors, disaggregating three biomass extraction sectors (agriculture, forestry and fishing) and one aggregated mining and quarrying sector. This resembles the structure of the OECD ICIO tables (with two material extraction sectors) and we expect similar results for the per-capita material footprint generated with the full model.

- GTAP has a proximity to EXIOBASE, as the biomass sectors in EXIOBASE were defined identically as those in GTAP, suggesting that results for the biomass footprint might be similar to the one produced with EXIOBASE. Regarding the extraction of abiotic materials, GTAP only features 4 sectors (coal, oil, gas, other mining). These features did not justify the inclusion of GTAP in this study.

- The comparison of all 5 available databases would have multiplied the efforts to perform pair-wise analyses (i.e. 10 pairs), which was beyond the scope of this study.

EXIOBASE

The EXIOBASE database was developed in several European research projects (EXIOPOL, CREEA and DESIRE) and particularly designed for environment-related applications. EXIOBASE is owned by a consortium of six research institutions, under the coordination of TNO Netherlands.

National IO tables serve as the basic data source and starting point for further disaggregation, to represent and differentiate crucial sectors with environmentally-sensitive activities (Wood et al., 2015). An industry-technology assumption is applied to transform the supply-use tables into symmetric input-output tables (Stadler et al., 2018).

EXIOBASE version 3 distinguishes 200 products (and 163 industries) of which 33 products refer to extraction of biotic and abiotic raw materials (Tukker et al., 2013). The material satellite data from the UNEP database could thus be used in its original detail in almost all material categories. EXIOBASE is the database with the highest level of sector detail at the level of all countries included for calculations of demand-based indicators of material flows (Stadler et al., 2018).

In terms of regional detail, EXIOBASE has a clear focus on the EU. The EU-28 and their 16 most important trading partners are explicitly modelled in EXIOBASE 3, representing about 95% of global GDP (Wood et al., 2015). The rest of the world is aggregated into five separate "Rest of" regions. All in all, version 3 comprises 49 regions and countries.

EXIOBASE 3 has been constructed as annual time series for the period of 1995 to 2011. The MR IOTs in both product-by-product and industry-by-industry format can be downloaded from http://www.exiobase.eu/index.php/data-download/exiobase3mon.

Eora

The Eora database is the most detailed MRIO database currently available. Eora was established at the University of Sydney (Lenzen et al., 2013) and is now owned by a small consulting company (KGM Associates). Eora data are freely available from the website www.worldmrio.com.

Eora comprises data for 189 individual countries plus one "rest of the world" region. The sector detail for each country in the multi-regional supply-use and input-output tables ranges between 26 (for many developing countries) and more than 400 sectors (in some industrialised countries such as Japan, the UK and the USA), thus totalling more than 15,000 sectors in the full Eora system. As the sectoral detail and thus the number of economic sectors related to material extraction is very different from country to country, the allocation of the various raw material inputs to economic sectors varies among countries but is based on similar concordance rules. Eora is available in yearly time series from 1970 to 2013. To arrive at a symmetric aggregated version of 26 sectors, which was taken as the starting point for the aggregation into the CC in this study, an industry-technology assumption is applied.

The philosophy of Eora, described in detail in Lenzen et al. (2013), is to include as much available official statistical data as possible and use official national input-output tables or trade data at the level of detail available in each country without harmonisation to a level of common sector and geographical detail. A mathematical framework was developed that allowed for the consideration of all available source data during the MRIO compilation process, ensuring that all available raw datasets are accurately represented within Eora. In cases where data sourced from different raw datasets presents misaligned, disparate and conflicting information, the reconciliation algorithm of Eora calculates a "best-fit" solution. Eora is the only MRIO database that also integrates reliability information for every data point.

During the construction of Eora, a strong focus was placed on application to different global environmental issues. Eora thus includes extensive satellite blocks covering a large number of environmental indicators such as GHG emissions, land use, water use and energy use. Eora has also been employed for a material footprint of consumption account using a detailed global, multi-country material extraction satellite (Wiedmann et al., 2015).

OECD ICIO

For the calculations underlying this paper, the 2015 edition of the OECD's Inter-Country Input-Output (ICIO) database (June 2015) was used. The database comprises 61 countries (accounting for approximately 95% of global GDP), including all 35 OECD member states, as well as non-OECD EU and G20 countries, and most ASEAN and APEC economies. A "Rest of the World" aggregate (RoW) is also included for completeness. Inter-sectoral trade flows are modelled for 34 industries based on ISIC Revision 3, of which there are two primary sectors ("Agriculture, hunting, forestry and fishing" and "Mining and quarrying"). The 2015 edition provided tables the years 1995, 2000, 2005, 2008–2011, available online for free.[1]

To construct the ICIO, maximum use is made of available official statistics, drawing on international sources (OECD, UNSD, Eurostat) and, in many cases, national sources. Latest *SNA93*[2] National Accounts main aggregate time series (including exports and imports) are compiled and validated, for more than 200 countries, to provide the principle constraints for the target countries and RoW. National Supply and Use tables (SUTs) and Input-Output tables (IOTs) are collected for all available years and harmonised (e.g. converted to target 34 industries/product groups and with consistent final demand structures). For industry constraints, SNA93 time series of value added and output for target industries are generated (using SBS from OECD, Eurostat or UNIDO to fill gaps when necessary). Bilateral merchandise trade in goods, from UN Comtrade, and bilateral Trade in Services, from BPM5 Balance of Payments statistics, are also crucial inputs. Finally, Household consumption by product (SNA93) and Tourism Satellite Accounts (TSA) statistics are also required. Building the ICIO requires many interconnected balancing procedures (drawing on methods outlined in Mattoo et al., 2013). The main strands are the development of time series (1995-2011) of (i) harmonised *national* Supply tables and Use tables *at purchasers' prices*; and (ii) balanced exports and imports of goods and services, *at purchasers' prices*, by the target industries/product groups. These results lead to the construction of harmonised domestic Use tables *at basic prices* and domestic import Use tables and then, inter-country Use tables - via the application of partner shares of cross-border trade by industry and end-use (intermediates and final demand). Final transformations using numerical balancing techniques yield national domestic (industry x industry) IOTs and, balanced inter-country flows of goods and services from industries to industries and final demand categories –

[1] In early 2017, a "light update" of the ICIO (ed. 2016) became available introducing two additional countries (Peru and Morocco) and covering all years from 1995 to 2011: http://oe.cd/icio

[2] A new version of ICIO, currently under construction makes use of latest SNA08 National Accounts and will use a modified industry list based on ISIC Rev. 4 and an extended set of product groups.

all at basic prices – which are then combined to produce the ICIO tables for each year, following an industry-technology assumption.

The following table summarizes the data sources and construction principles of the three applied GMRIO databases.

Table SI 1-1: Summary of data and construction notes for Eora, EXIOBASE and OECD ICIO (adapted from Steen-Olsen et al., 2016)

Eora

Source data	National IO tables	74 tables from national statistical offices Other countries' data taken from UN National Accounts Main Aggregates Database and applied to a general template averaged from Australia, Japan and the US
	Bilateral trade data	Trade in goods from UN Comtrade database Trade in services from UN Service trade database
	Global estimates	UN National Accounts Main Aggregates Database
System structure	Country/region detail	189 countries and 1 rest-of-world region
	Sector detail	Varies by country; ranges from 25 to 511 sectors
	Structure of IO tables	Heterogenous table structure Mix of SUT and IOT IOT can be ixi or pxp
	Time series	1990-2016
System construction	Harmonization of sectors	Uses original classifications from national accounts
	Harmonization of prices and currency	Converts national currencies into current US$ using exchange rates from IMF
	Dealing with transit trade	Re-imports/exports are a separate column at the end of each country's data
	Off diagonal trade data calculations, balancing and constraints	All data subject to large-scale KRAS optimisation of an initial MRIO estimate with numerous constraints

EXIOBASE

Source data	National IO tables	EU28 (and Norway & Turkey) data from Eurostat Other nations data from national statistical offices
	Bilateral trade data	BACI database (based on Comtrade) UN Service trade database
	Global estimates	UN National Accounts Main Aggregates Database
System structure	Country/region detail	44 countries; 5 rest-of-world regions
	Sector detail	163 industries; 200 products
	Structure of IO tables	Homogenous SUT tables
	Time series	1995-2011
System construction	Harmonization of sectors	Use concordances to convert original classifications into EXIOBASE sectors
	Harmonization of prices and currency	Original data is converted to technical coefficients and then matched to the UN Global estimates. Exchange rates used to convert to Euros
	Dealing with transit trade	Re-exports of each product are subtracted from import use.
	Off diagonal trade data calculations, balancing and constraints	Uses quadratic programming optimisation method to balance the table subject to certain parameters

ICIO

Source data	National IO tables	Member counties submit tables in the format required for OECD, UNSD & Eurostat
	Bilateral trade data	OECD Bilateral Trade database
System structure	Country/region detail	61 countries and 1 rest-or-world region
	Sector detail	34 sectors
	Structure of IO tables	Homogenous ixi IOTs
	Time series	1995-2011
System construction	Harmonization of sectors	Tables are harmonized to consistent 34 sector groupings using concordances
	Harmonization of prices and currency	SUT tables harmonised in USD purchasers prices. Then domestic use tables produced in basic prices.
	Dealing with transit trade	In construction of ICIO for partner shares of trade in goods, reported imports are prioritised as initial values[3]. The trade statistics used are adjusted for re-exports (Mattoo et al., 2013).
	Off diagonal trade data calculations, balancing and constraints	Apply partner shares to determine cross-border trade. Numerical balancing techniques used

[3] www.gee.gov.pt/wwwbase/wwwinclude/ficheiro.aspx?access=1&id=33209.

2. Countries and sectors in the common classification

The following table provides an overview of the 40 countries and the 'Rest of the world' regions included in the common classification.

Table SI 1-2: Country list in common classification

Region	Country Code	Country Name
EU	AT	Austria
	BE	Belgium
	BG	Bulgaria
	CY	Cyprus
	CZ	Czech Republic
	DE	Germany
	DK	Denmark
	EE	Estonia
	ES	Spain
	FI	Finland
	FR	France
	GR	Greece
	HU	Hungary
	IE	Ireland
	IT	Italy
	LT	Lithuania
	LU	Luxembourg
	LV	Latvia
	MT	Malta
	NL	Netherlands
	PL	Poland
	PT	Portugal
	RO	Romania
	SE	Sweden
	SI	Slovenia
	SK	Slovakia
	UK	United Kingdom
Americas	BR	Brazil
	CA	Canada
	MX	Mexico
	US	United States of America
Asia	CN	China
	ID	Indonesia
	IN	India
	JP	Japan
	KR	Korea, Republic of
	RU	Russian Federation
	TR	Turkey
	TW	Taiwan
	AU	Australia
	RW	Rest of the world

The next table lists the industries discerned in the common classification.

Table SI 1-3: Industry group list in common classification

Sector number	Industry group	Abbreviation in figures
1	Agriculture, hunting, forestry, fishing	Agriculture
2	Mining, quarrying	Mining
3	Production of food, beverages, tobacco	Food
4	Production of textiles, leather, wearing apparel	Textiles
5	Wood, paper, publishing	Wood/paper
6	Production of petroleum, chemicals, non-metallic minerals	Petroleum/chemicals
7	Manufacturing of metal products	Metal products
8	Manufacturing of electrical machinery	Elec. machinery
9	Manufacturing of transport equipment	Transport equipment
10	Other manufacturing, recycling	Manufacturing recycling
11	Electricity, gas, water	Electricity/gas/water
12	Construction	Construction
13	Sale, maintenance, repair of vehicles, fuel trade	Sale
14	Transport	Transport
15	Post, telecommunications	Post & telec.
16	Financial intermediation, business activity	Financial activities
17	Public administration, education, health, recreation, other services	Public admin./health

3. Descriptions of SDA and SPLD methods

Structural Decomposition Analysis (SDA) is a decomposition method based on input-output models that allows breaking down the changes in a dependent variable into the changes in its determinants. In the course of such an analysis, the Leontief inverse (L) usually remains a single entity. Nevertheless, due to the fact that the elements in the Leontief inverse are the result of a matrix inversion ($\mathrm{L} = (\mathrm{I} - \mathrm{A})^{-1}$), where I stands for the identity matrix, each value in the inverse L depends on many different values in the technology matrix A. Structural Production Layer Decomposition (SPLD) is using a power series expansion ($\mathrm{L} = \mathrm{I} + \mathrm{A} + \mathrm{A}^2 + \mathrm{A}^3 + \cdots$) to disaggregate the inverse and by that means revealing the actual technology coefficients that are related to the values i.e. elements in the inverse (and the effects thereof). SDA and SPLD complement each other. A very detailed description of the SPLD methodology can be found in Wieland et al. (2018), for a more detailed description of a similar SDA analysis we refer to Owen et al. (2014). The following section provides only brief descriptions of both methods, starting with SDA and followed by SPLD.

Structural Decomposition Analysis (SDA)

The SDA model used in the present study structurally decomposes the difference in country material footprints of two MRIO models ($\Delta \mathrm{D} = \mathrm{D}_1 - \mathrm{D}_2 = \mathrm{F}\hat{\mathrm{x}}_1{}^{-1}\mathrm{L}_1\mathrm{y}_1 - \mathrm{F}\hat{\mathrm{x}}_2{}^{-1}\mathrm{L}_2\mathrm{y}_2$) into effects stemming from differences in the Leontief inverse (L), the final demand (Y) and gross production vector (x). The fact that all MRIO models use identical raw material extraction accounts ($\mathrm{F} = \mathrm{F}_1 = \mathrm{F}_2$) leads to a decomposition equation with three terms:

$$\Delta \mathrm{D} = \mathrm{x}^{effect} + \mathrm{L}^{effect} + \mathrm{y}^{effect}$$

where y^{effect} represents the contribution of the differences in a final demand vector ($\Delta \mathrm{y} = \mathrm{y}_2 - \mathrm{y}_1$) to the total material footprint difference $\Delta \mathrm{D}$ and so forth. This study builds on the Shapely-Sun (S-S) decomposition approach (compare Ang, 2004; Sun, 1998), which is basically the mean effect of the (full n!) D&L decomposition approach (Dietzenbacher and Los, 1998). Following the S-S approach, we can calculate the three effects for a single extraction vector (f) by:

$$\mathrm{x}^{effect} = \mathrm{f}\left[\Delta\hat{\mathrm{x}}^{-1}\mathrm{L}_1\mathrm{y}_1 + \tfrac{1}{2}\Delta\hat{\mathrm{x}}^{-1}(\Delta\mathrm{L}_1\mathrm{y}_1 + \mathrm{L}_1\Delta\mathrm{y}) + \tfrac{1}{3}\Delta\hat{\mathrm{x}}^{-1}\Delta\mathrm{L}\,\Delta\mathrm{y}\right],$$

$$\mathrm{L}^{effect} = \mathrm{f}\left[\hat{\mathrm{x}}_1{}^{-1}\Delta\mathrm{L}\,\mathrm{y}_1 + \tfrac{1}{2}\left(\Delta\hat{\mathrm{x}}^{-1}\Delta\mathrm{L}\,\mathrm{y}_1 + \hat{\mathrm{x}}_1{}^{-1}\Delta\mathrm{L}\,\Delta\mathrm{y}_1\right) + \tfrac{1}{3}\Delta\hat{\mathrm{x}}^{-1}\Delta\mathrm{L}\,\Delta\mathrm{y}\right],$$

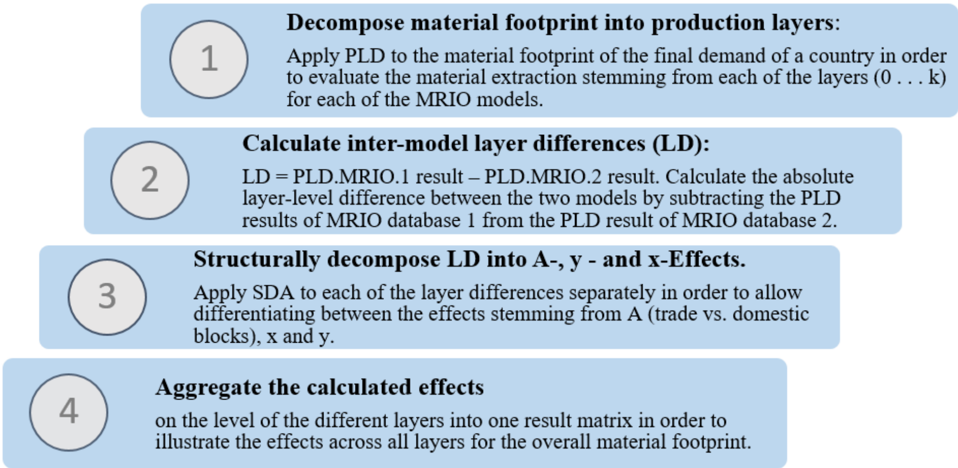
$$\mathrm{y}^{effect} = \mathrm{f}\left[\hat{\mathrm{x}}_1{}^{-1}\mathrm{L}_1\,\Delta\mathrm{y} + \tfrac{1}{2}\left(\Delta\hat{\mathrm{x}}^{-1}\mathrm{L}_1\,\Delta\mathrm{y} + \hat{\mathrm{x}}_1{}^{-1}\Delta\mathrm{L}\,\Delta\mathrm{y}_1\right) + \tfrac{1}{3}\Delta\hat{\mathrm{x}}^{-1}\Delta\mathrm{L}\,\Delta\mathrm{y}\right], \text{ where}$$

$$\Delta\mathrm{x} = \mathrm{x}_2 - \mathrm{x}_1,$$

$$\Delta \mathrm{L} = \mathrm{L}_2 - \mathrm{L}_1 \text{ and}$$
$$\Delta \mathrm{y} = \mathrm{y}_2 - \mathrm{y}_1.$$

Structural Production Layer Decomposition (SPLD)

The central idea of SPLD is a structural decomposition that uses the technology matrix A instead of the Leontief inverse L. SPLD structurally decomposes a set of PLD (production layer decomposition) results (see for example Giljum et al., 2016). Just like the SDA model described before, SPLD also applies the S-S approach. The SPLD calculation is carried out in the following four steps (Wieland et al., 2018):



First, decompose material footprints into single production layers: $\mathrm{E}_k = \hat{\mathrm{f}}\,\hat{\mathrm{x}}^{-1}\mathrm{A}^k\hat{\mathrm{y}}$, where the matrix E_k equals the raw material extraction on the production layer (i.e. tier) k of a product supply chain which directly or indirectly serves final demand y. The hat-notation (^) indicates diagonalization of the vector. Because there is an infinite number of layers, SPLD requires the selection of a threshold (r), which defines the last layer that is separately analysed i.e. decomposed. Subsequently, we calculate a residual E_{rest} in order to relate the layer results E_k to the total material footprint MF via

$$\mathrm{L}_{rest} = \mathrm{L} - \textstyle\sum_{k=0}^{r} \mathrm{A}^k ,$$
$$\mathrm{E}_{rest} = \hat{\mathrm{f}}\,\hat{\mathrm{x}}^{-1}\mathrm{L}_{rest}\,\hat{\mathrm{y}} \text{ and}$$
$$\mathrm{D} = \left(\textstyle\sum_{k=0}^{r} \mathrm{E}_k\right) + \mathrm{E}_{rest}.$$

For the present analysis, we choose to decompose the material footprints up to layer five ($r = 5$). On average, the aggregated material footprint up to layer five comprises between 85 - 95% of the total country footprint. Second, calculate the layer differences for the model pair: $\mathrm{LD}_k = \mathrm{E}_k{}^{\mathrm{MRIO2}} - \mathrm{E}_k{}^{\mathrm{MRIO1}}$. Third, decompose LD_k

into effects stemming from differences in the technology matrix (A), the gross production (x) and final demand vector (y). Again, all MRIO models use identical raw material extraction vectors ($\mathrm{f} = \mathrm{f}_1 = \mathrm{f}_2$). This yields for the k-th layer difference a decomposition equation with $(k+2)$ terms:

$$\Delta \mathrm{LD}_k = \hat{\mathrm{x}}_k^{effect} + \mathrm{A}_{k,m=1}^{effect} + \cdots + \mathrm{A}_{k,m=k}^{effect} + \hat{\mathrm{y}}_k^{effect}$$

Effects stemming from the differences in gross production ($\hat{\mathrm{x}}_k^{effect}$) and final demand vector ($\hat{\mathrm{y}}_k^{effect}$) are calculated applying the traditional standard S-S approach. In order to calculate the matrix A^{effect}, where element i.e. cell $a_{i,j}^{effect}$ represents the contribution of the differences in the technology matrix element $a_{i,j}$ to the total material footprint difference, SPLD uses a modified matrix multiplication approach which can be written for the k-th layer and the m-th segment as:

$$\mathrm{A}_{k,m}^{effect} = \left[\,\hat{\mathrm{f}}\,\hat{\mathrm{x}}_1^{-1}\mathrm{A}_1^{k-m}\right]' \mathrm{J}\,[\mathrm{A}_1^{m-1}\hat{\mathrm{y}}_1]' \circ \Delta\mathrm{A}$$

where J is a matrix of ones with the same size as A and $\Delta\mathrm{A} = \mathrm{A}_2 - \mathrm{A}_1$. The ' indicates a transposition and $\circ$ an element –wise multiplication of two matrices, termed the Hadamard product. After having calculated all effects for all layers and segments, the final and last step is to aggregate the result matrices:

$$\hat{\mathrm{x}}^{total} = \sum_{k=0}^{r} \hat{\mathrm{x}}_k^{effect},$$

$$\mathrm{A}^{total} = \sum_{k=1}^{r} \sum_{m=1}^{k} \mathrm{A}_{k,m}^{effect},$$

$$\hat{\mathrm{y}}^{total} = \sum_{k=0}^{r} \hat{\mathrm{y}}_k^{effect},$$

$$\sum_{k=0}^{r} \mathrm{LD}_k = \hat{\mathrm{x}}^{total} + \mathrm{A}^{total} + \hat{\mathrm{y}}^{total}.$$

Please note that when the main text refers to the A-effect matrix of the SPLD calculation, this is A^{total}. One issue to be aware of is the dependency problem in SDA and SPLD, where it is assumed that all variables are independent of each other (Dietzenbacher and Los, 2000). In our work, we could expect that there is some dependency between the size of L and x as well as x and y. There is no clear way to avoid dependencies (Minx et al., 2011). One option to reduce the dependencies in our assessment is to harmonize the different GMRIO tables with regard to the total gross production. A certain proportion of the x-effect stems from the simple fact that the different GMRIOs report different total gross production values, which in principle could be reduced by scaling the different GMRIO to the same totals. Manipulating the GMRIOs in such a way has no effect on the material footprint results and the differences thereof. Therefore, we leave this to future research.

4. Country results in full and CC classifications

The following table lists the material footprint per capita results for all three models in both the full and the common classification. In the block to the right, the percentage differences between the two aggregation levels are illustrated, comparing the full models with the CC. A green bar indicates higher numbers in the CC compared to the full model.

Table SI 1-4: Material footprint per capita, three GMRIO models, full detail and CC

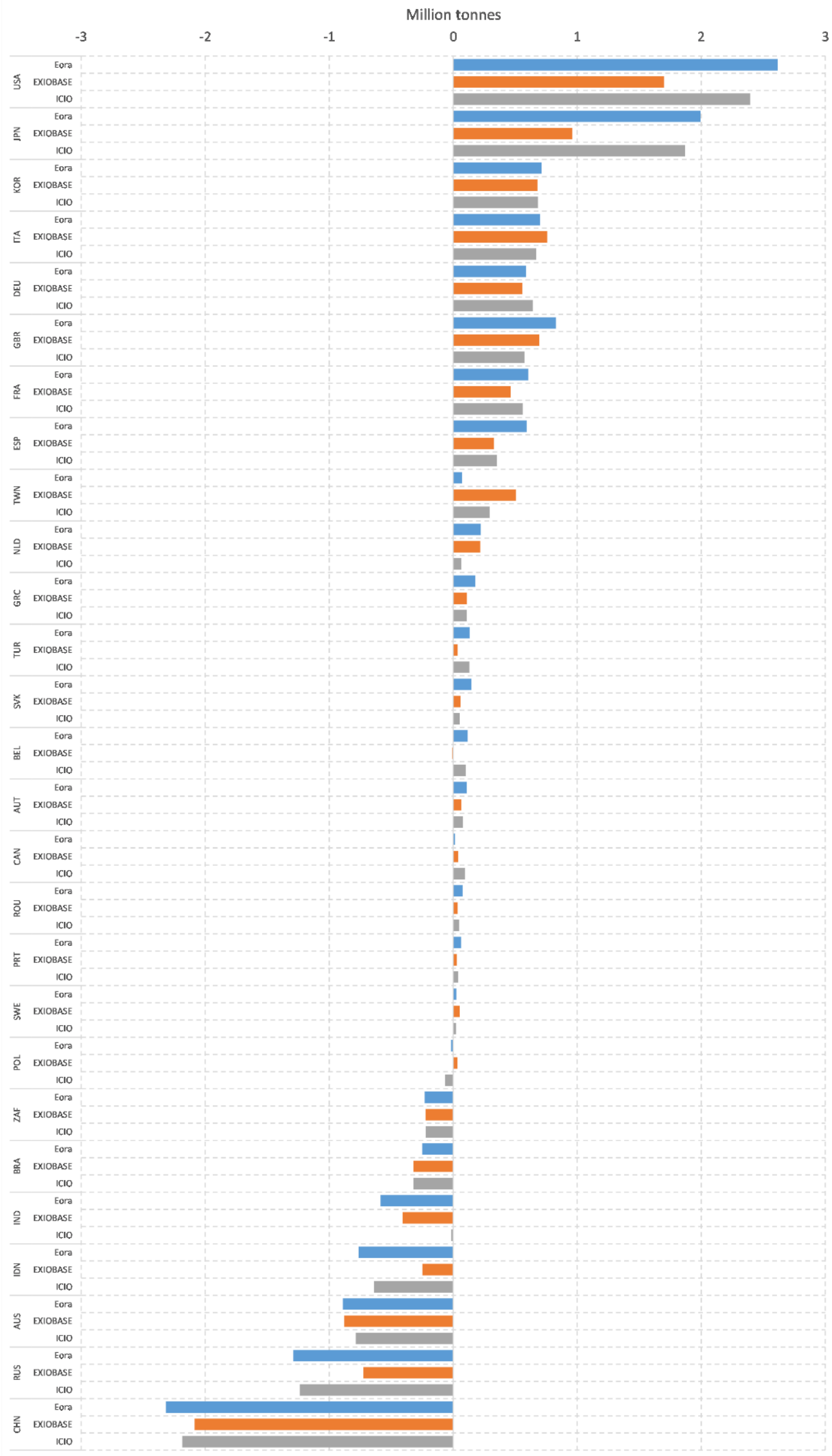
	Eora	EXIOBASE	ICIO	Eora_{cc}	EXIOBASE_{cc}	ICIO_{cc}	Eora (%)	EXIOBASE (%)	ICIO (%)
AUS	38.0	38.5	42.6	36.3	53.0	42.9	-4.5	37.4	0.8
AUT	30.0	25.0	26.4	31.2	26.0	26.1	4.2	3.9	-1.1
BEL	19.3	22.6	17.9	33.1	28.7	18.2	71.3	27.1	1.7
BGR	10.4	14.8	12.1	10.1	14.3	12.1	-2.2	-3.6	-0.3
BRA	13.0	12.6	12.6	14.4	11.7	12.5	11.0	-7.5	-0.7
CAN	28.5	29.3	30.8	30.5	32.3	31.7	7.1	10.5	2.8
CHN	15.0	15.2	15.1	14.3	14.6	14.8	-5.0	-3.9	-1.7
CYP	24.1	20.9	23.8	25.7	22.4	22.4	6.6	6.8	-6.3
CZE	21.3	19.7	20.3	21.7	20.2	20.3	1.7	2.5	-0.2
DEU	21.4	21.1	22.1	26.2	25.4	22.6	22.3	20.7	2.3
DNK	23.9	23.2	25.4	29.9	25.3	27.4	25.1	8.8	8.1
ESP	23.1	17.4	17.9	24.1	18.2	18.2	4.5	4.4	1.3
EST	18.1	24.5	21.8	25.7	27.2	22.9	42.0	10.8	5.1
FIN	34.5	24.9	28.9	36.3	36.0	30.6	5.4	44.8	6.0
FRA	20.0	17.9	19.3	23.6	20.6	19.9	17.7	15.5	2.9
GBR	19.2	17.1	15.2	20.8	17.6	16.9	8.3	3.0	11.0
GRC	28.4	18.6	22.1	27.2	23.2	22.9	-4.3	24.9	3.8
HUN	13.0	14.6	14.4	14.3	13.9	14.3	10.2	-4.8	-0.4
IDN	5.0	7.2	5.5	5.9	7.9	5.6	16.5	10.4	0.2
IND	3.6	3.7	4.0	3.4	4.1	4.0	-5.8	10.6	0.0
IRL	25.9	32.1	23.4	23.0	33.5	25.0	-11.0	4.1	7.0
ITA	19.6	20.6	19.0	19.2	20.2	20.1	-1.8	-1.9	5.3
JPN	20.0	11.9	19.0	23.3	16.2	17.5	16.7	36.0	-7.6
KOR	22.8	22.1	22.2	23.4	21.6	22.5	2.9	-2.5	1.6
LTU	24.9	16.2	13.5	28.7	16.1	13.6	15.0	-0.8	0.7
LVA	21.2	17.8	16.3	18.9	17.5	17.0	-10.8	-1.7	4.3
MEX	8.4	8.3	8.7	8.1	8.5	8.9	-3.7	1.4	2.1
MLT	20.3	18.1	16.9	16.5	21.1	14.4	-19.1	16.7	-15.1
NLD	23.5	19.8	13.9	38.9	27.2	14.7	65.6	37.7	5.7
POL	16.4	17.8	15.1	17.8	17.2	15.3	8.2	-3.6	1.2
PRT	22.1	18.9	19.8	23.3	20.2	20.4	5.4	6.6	3.1
ROU	14.3	12.4	13.0	16.0	12.3	13.0	11.8	-0.4	-0.2
RUS	8.1	12.0	8.4	5.3	10.8	8.7	-34.4	-10.1	4.0
SVK	37.5	21.3	20.2	40.2	18.8	20.1	7.1	-11.6	-0.2
SVN	22.5	21.0	23.4	22.2	22.4	22.8	-1.3	6.9	-2.4
SWE	23.6	26.7	23.3	27.1	30.0	24.7	15.1	12.2	6.1
TUR	12.8	11.4	12.7	12.7	12.2	12.9	0.0	7.1	1.0
TWN	9.1	21.9	18.7	7.5	20.2	19.5	-18.1	-7.9	4.2
USA	27.3	24.3	26.5	32.7	27.6	27.2	20.1	13.7	2.3

5. Raw Material Trade Balance (RTB) of three GMRIO models

The following figure illustrates the RTB indicator calculated with the three MRIO models. The RTB is calculated as the Raw Material Equivalents (RMEs) of imports minus the RMEs of exports. For the figure, a selection is made for those countries, for which the RTB indicates a positive or negative value of 50 million tonnes or higher in at least one of the three models.

The figure shows that the models produce comparable results with regard to countries being either net-exporters or net-importers of raw materials. Exceptions in the sample are Poland and Belgium, for which EXIOBASE delivers a different prefix compared to the other two MRIO models.

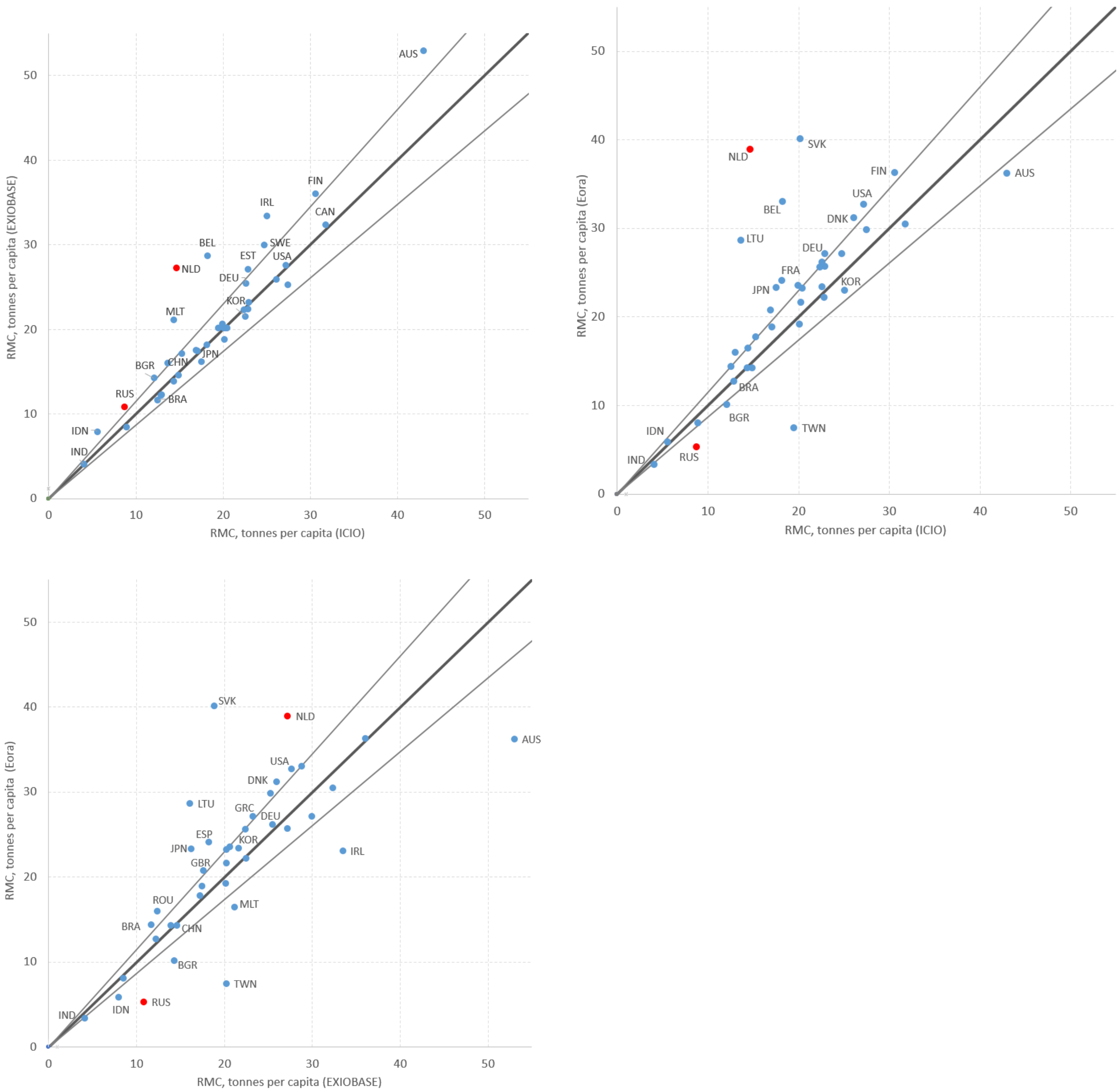
Figure SI 1-1: Raw Material Trade Balance (RTB) of selected countries, 2010



6. Comparison of MF per capita, model-pairs in the CC

The following figure illustrates the deviations of material footprints per capita between the three model pairs, calculated with the common classification. As in Figure 1in the main text, countries outside the corridor of 15% deviation are illustrated and major countries within the defined range of deviations. Results for all countries can be found in chapter 4 above.

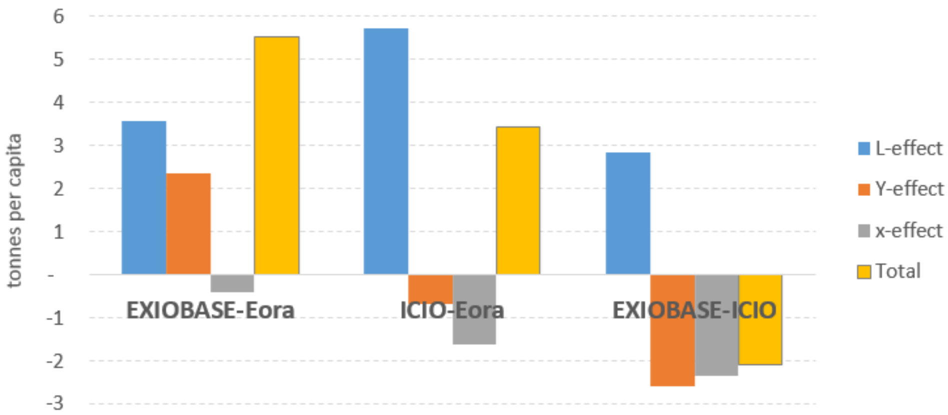
Figure SI 1-2: Comparison of material footprints per capita, three model pairs, common classification, 2010



7. SDA and SPLD analyses for Russia

Figure SI 1-3 presents the SDA results for the three model pairs for the material footprint per capita of Russia.

Figure SI 1-3: MF per capita of Russia, 2010, SDA of three GMRIO pairs

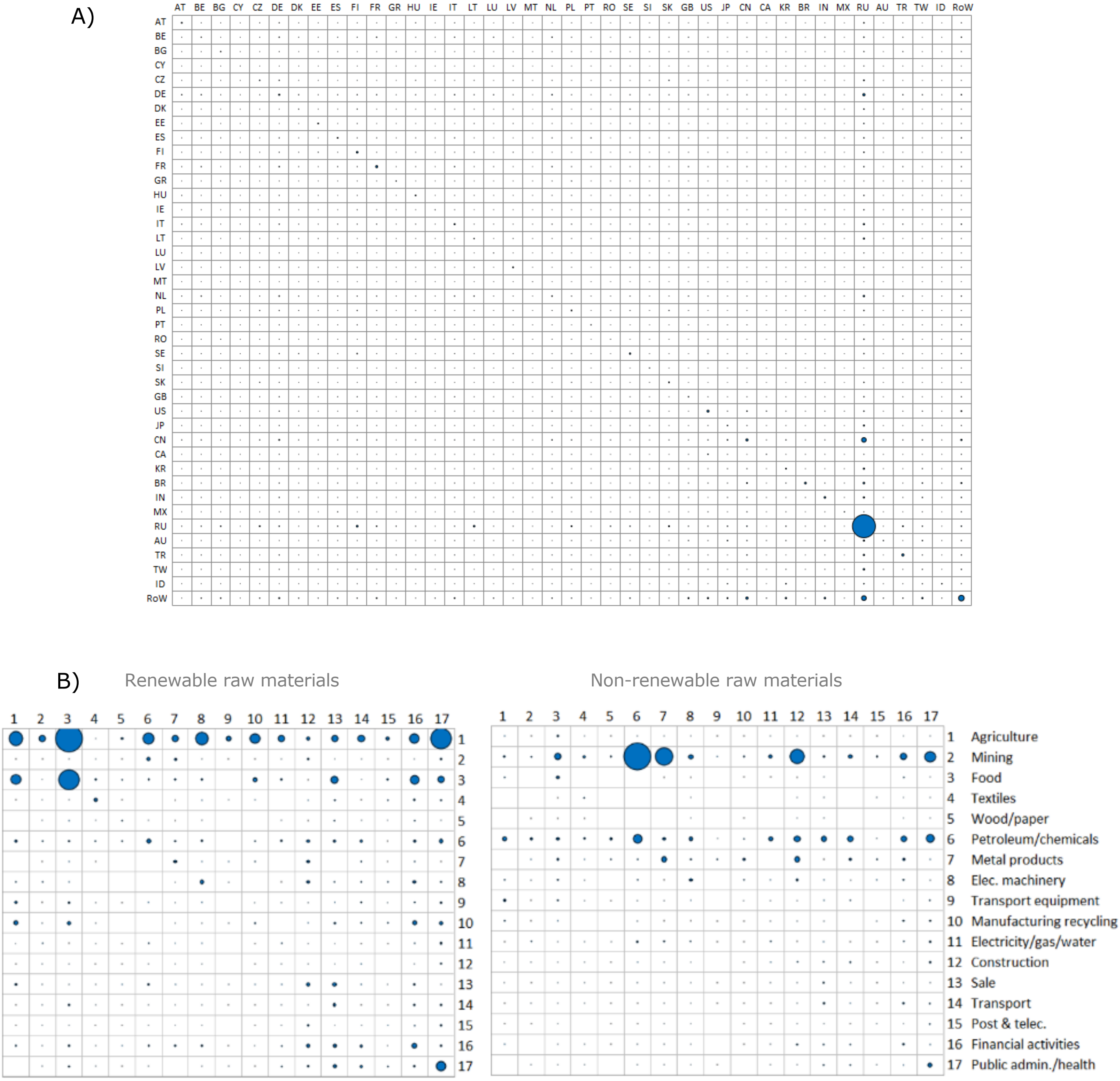


Performing a SDA allows identifying the main factors in the GMRIO models that cause the observed deviations. For example, the total difference of 5.5 tonnes per capita between the Eora$_{cc}$ and EXIOBASE$_{cc}$ models is mostly explained by effects stemming from the Leontief inverse matrix (L-effect; +3.6 tonnes per capita in EXIOBASE$_{cc}$ as compared to Eora$_{cc}$) and differences in the final demand data (Y-effect; +2.4 tonnes). In contrast, the differences in the total output (x-effect) would result in a material footprint that is only 0.4 tonnes per capita smaller in EXIOBASE$_{cc}$ as compared to Eora$_{cc}$.

Looking at the SDA results of the other two model pairs reveals that across the three model pairs the L-effect (in absolute values) is stronger than the y- and the x-effect. This result points to the importance of the inter-industry part for the results of material footprint indicators. The difference is most remarkable in the case of the ICIO$_{cc}$-Eora$_{cc}$ pair and smallest regarding the EXIOBASE$_{cc}$-ICIO$_{cc}$ pair.

Figure SI 1-4 illustrates the SPLD result for Russia from a country perspective, taking the EXIOBASE$_{cc}$-Eora$_{cc}$ pair as an example. The graphs for the other two model pairs are available in chapter 8.

Figure SI 1-4: SPLD results for the MF of Russia, country perspective (A), sector perspective (B), EXIOBASE$_{cc}$-Eora$_{cc}$ pair, 2010



Note: the size of the bubbles is scaled for each graph separately, in order to best illustrate the deviation patterns for each specific aggregation and material group. Bubble sizes across figures can therefore not be directly compared.

Figure SI 1-4 (A) illustrates that the deviations observed in the MF of Russia calculated with $EXIOBASE_{cc}$ and $Eora_{cc}$ largely arise from differences in the domestic data of Russia itself, which explains 68% of all deviations. All other domestic and trade blocks of the multi-regional matrix contribute only to a smaller extent to the differences in the material footprint.

After having identified the 'geographical hot spot', the next level of analysis tackles the dimension of inter-industry flows from a sector perspective. In Figure SI 1-4 (B), we illustrate, which differences of the renewable (biotic) and non-renewable (abiotic) material footprints stemming from the A-matrix can be attributed to the different inter-sectoral flows. Note that the figure comprises all global supply-chains that serve final demand in Russia. We separate the two groups of raw materials, as they are used in different supply chains and contribute differently to the total deviations stemming from the A-matrix: 88% are related to non-renewable raw materials and only 12% to renewable raw materials.

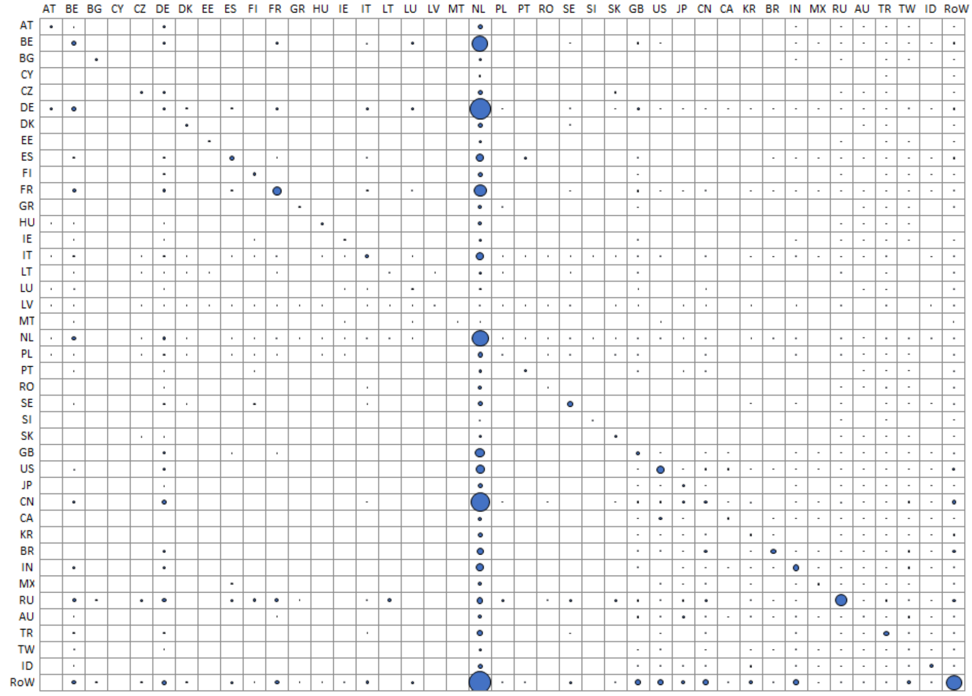
Figure SI 1-4 (B) reveals clear sectoral hot spots and supply chains, which cause the variation in model results. As expected, for renewable raw materials, the deliveries from the agricultural (incl. forestry) sector to the food sector alone explain 20% to the differences stemming from the A-matrices on the diverging biomass footprint. In addition, deliveries to the public administration and health sector as well as inner-sectoral use of biomass by the food sector contribute 11% each. Data deviations in sectors further up the supply-chains, including the service sectors, only contribute to a small extent to the overall difference.

The high importance of the first stages of the supply-chains is also clearly visible in the case of non-renewable raw materials. The deliveries of the mining sector to the petroleum and chemicals sector contribute by 31% to the total differences in the non-renewable raw material footprint. Deliveries to the metal production (13%) and construction (9%) sectors are also hotspots of high impact on the overall result. The dominant role of the petroleum sector in Russia is visible further upstream, i.e. deliveries from this sector to other manufacturing and service sectors have visible effects. Again, the lower part of the chart illustrates that data deviations further downstream in supply chains, i.e. related to higher manufactured products and services, have only a small impact.

8. SPLD results for additional model pairs

Netherlands

Figure SI 1-5: SPLD results for the RMC of the Netherlands, country perspective, EXIOBASE-Eora pair (above), EXIOBASE-ICIO pair (below), 2010



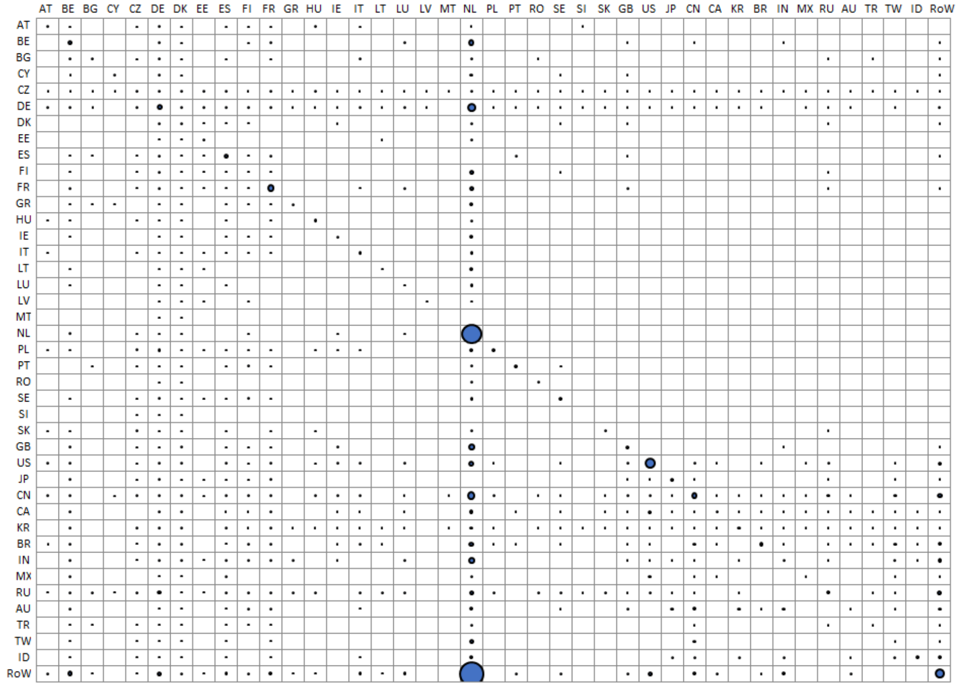
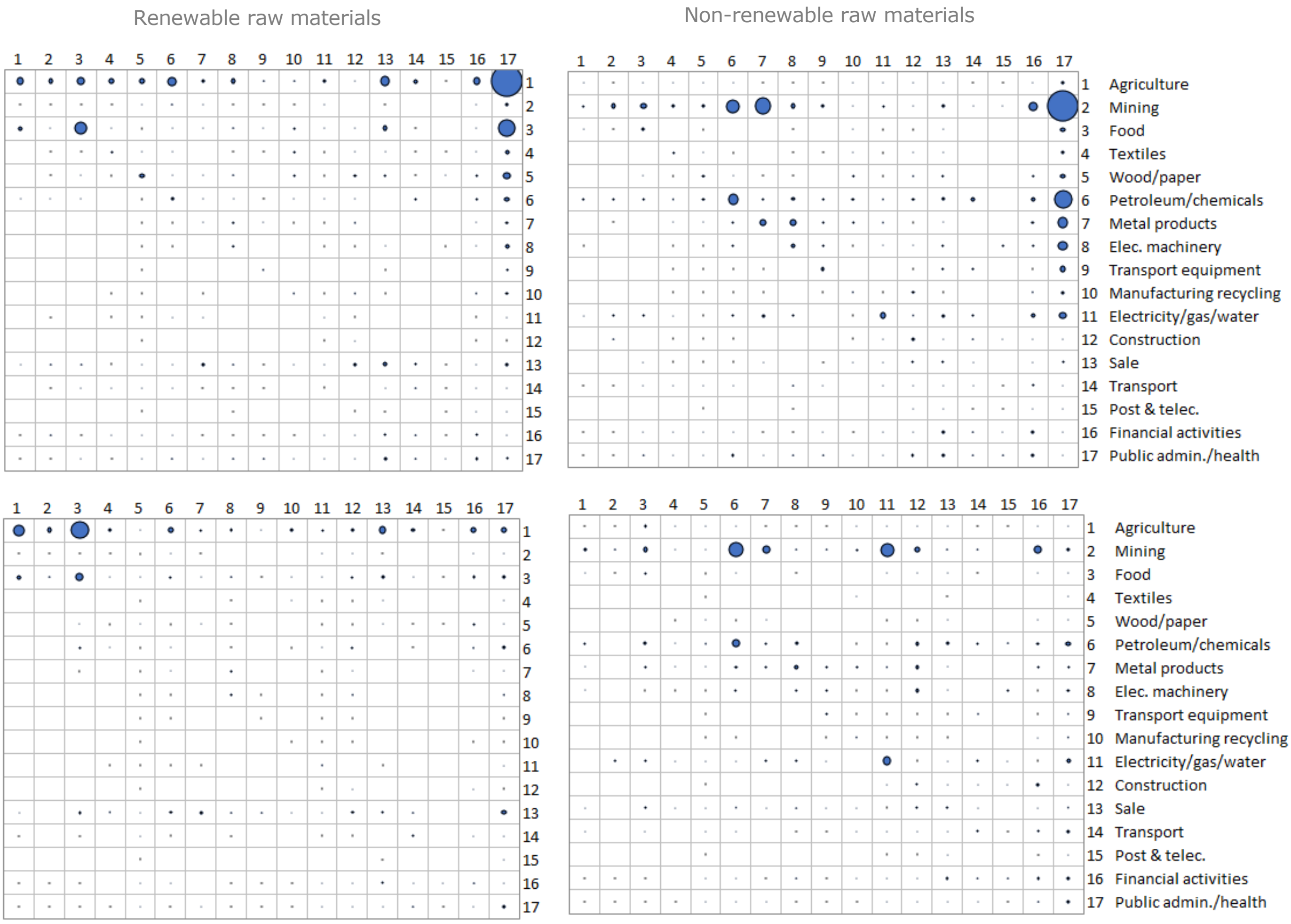


Figure SI 1-6: SPLD results for the MF of the Netherlands, sector perspective, EXIOBASE-Eora pair (above), EXIOBASE-ICIO pair (below), 2010



Russia

Figure SI 1-7: SPLD results for the MF of Russia, country perspective, EXIOBASE-ICIO pair (above), Eora-ICIO pair (below), 2010

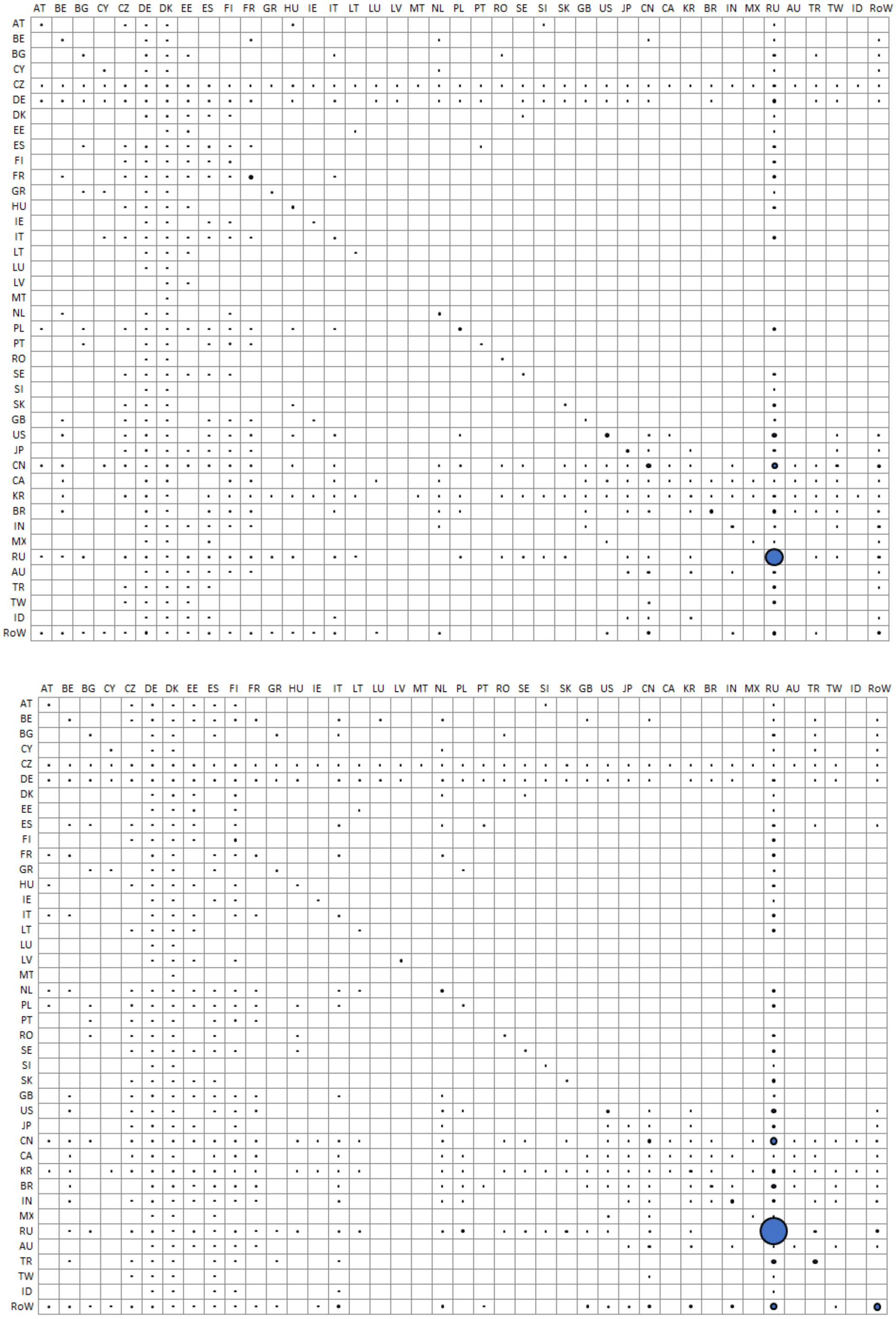
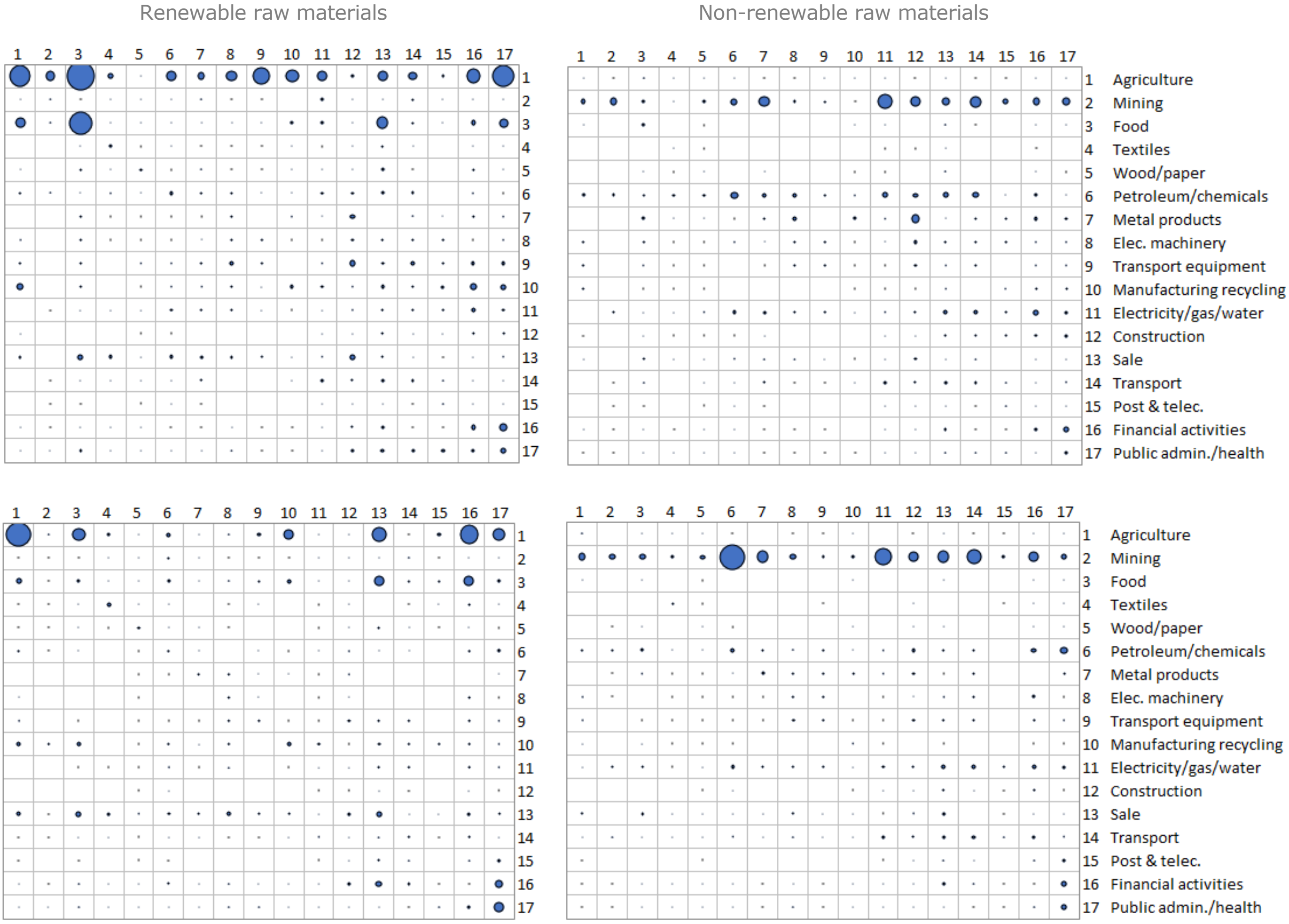


Figure SI 1-8: SPLD results for the MF of Russia, sector perspective, EXIOBASE-ICIO pair (above), Eora-ICIO pair (below), 2010



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